

Warm-up: 2 arms (A/B testing)

Input: 2 arms, $\mathfrak{S} \in \mathbb{N}$

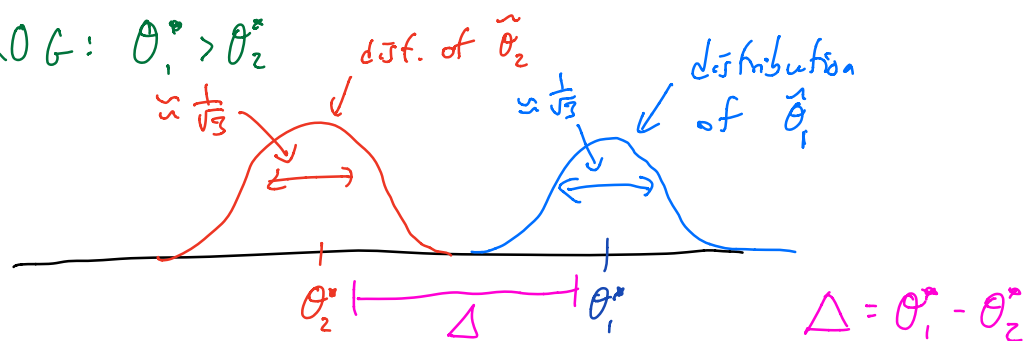
Pull each arm \mathfrak{S} times and observe $(X_{1,1}, \dots, X_{1,\mathfrak{S}})$
 $(X_{2,1}, \dots, X_{2,\mathfrak{S}})$

$$\hat{\theta}_i = \frac{1}{\mathfrak{S}} \sum_{s=1}^{\mathfrak{S}} X_{i,s}$$

For all $t > 2\mathfrak{S}$ play $\arg\max_i \hat{\theta}_i$ (Assume $\text{Var}(X_{i,1}) = O(1)$)

Goal: Analyze regret of this algorithm.

WLOG: $\theta_1^* > \theta_2^*$



Want \mathfrak{S} to be large enough so that

$$\theta_1^* > \theta_2^* \Rightarrow \hat{\theta}_1 > \hat{\theta}_2.$$

Intuitively $\frac{1}{\sqrt{\mathfrak{S}}} < \frac{\Delta}{2} \Rightarrow \mathfrak{S} \gg 4\Delta^{-2}$

Goal: Construct a confidence interval s.t. $|\hat{\theta}_i - \theta_i^*| > \varepsilon$
w.p. $\leq 1 - \delta$.

Let X_1, \dots, X_n be independent, identically distributed random variables. $\mathbb{E}[X_i] = 0$

$$\mathbb{P}\left(\frac{1}{n} \sum_{i=1}^n X_i > \varepsilon\right) \leq \delta.$$

Chebyshev's Inequality

$$\mathbb{P}\left(\frac{1}{n} \sum_{i=1}^n X_i > \varepsilon\right) \leq \mathbb{P}\left(\left(\frac{1}{n} \sum_{i=1}^n X_i\right)^2 > \varepsilon^2\right)$$

$$\leq \frac{\mathbb{E}\left[\left(\frac{1}{n} \sum_{i=1}^n X_i\right)^2\right]}{\varepsilon^2} \leftarrow \text{Markov's}$$

$$= \frac{\mathbb{E}\left[\sum_{i=1}^n X_i^2\right]}{n^2 \varepsilon^2}$$

$$= \frac{\text{Var}(X_1)}{n \varepsilon^2} \quad \left(\begin{array}{l} X_i \sim \mathcal{N}(0, \sigma^2) \\ \Rightarrow \frac{\sigma^2}{n \varepsilon^2} \end{array} \right)$$

Markov's Inequality For any positive R.V.

$$Z \text{ we have } \mathbb{P}(Z > \varepsilon) \leq \frac{\mathbb{E}[Z]}{\varepsilon}$$

$$\text{(Proof hint: } \mathbb{E}[Z] = \int_0^{\infty} \mathbb{P}(Z > t) dt \text{)}$$

Chernoff Bound Technique

Fix $\lambda > 0$.

$$\mathbb{P}\left(\frac{1}{n} \sum_{i=1}^n x_i > \varepsilon\right) = \mathbb{P}\left(\lambda \sum_{i=1}^n x_i > \lambda n \varepsilon\right)$$

$$= \mathbb{P}\left(\exp\left(\lambda \sum_{i=1}^n x_i\right) > \exp(\lambda n \varepsilon)\right)$$

$$\leq \frac{\mathbb{E}\left[\exp\left(\lambda \sum_{i=1}^n x_i\right)\right]}{\exp(\lambda n \varepsilon)} \quad \leftarrow \text{Markov}$$

By assumption $X_1 \perp X_2 \Rightarrow \mathbb{E}[g(x_1)g(x_2)] = \mathbb{E}[g(x_1)]\mathbb{E}[g(x_2)]$

$$= e^{-\lambda n \varepsilon} \mathbb{E}\left[\prod_{i=1}^n \exp(\lambda x_i)\right]$$

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$$= \exp(-\lambda n \varepsilon) \exp\left(n \log(\mathbb{E}[\exp(\lambda x_i)])\right)$$

$$= \exp\left(-\lambda n \varepsilon + \underbrace{n \log(\mathbb{E}[\exp(\lambda x_i)])}_{=: \psi_x(\lambda)}\right)$$

$$\Rightarrow \mathbb{P}\left(\frac{1}{n} \sum_{i=1}^n x_i > \varepsilon\right) \leq \exp\left(-n \left(\sup_{\lambda > 0} \lambda \varepsilon - \psi_x(\lambda)\right)\right)$$

$$\text{Ex. } X_i \sim \mathcal{N}(0, \sigma^2)$$

$$\mathbb{E}[\exp(\lambda X)] = \int e^{\lambda x} \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2}{2\sigma^2}} dx = e^{\lambda^2 \sigma^2 / 2}$$

$$\varphi_X(\lambda) = \lambda^2 \sigma^2 / 2$$

$$\begin{aligned} \sup_{\lambda} \lambda \varepsilon - \varphi_X(\lambda) &= \sup_{\lambda} \lambda \varepsilon - \lambda^2 \sigma^2 / 2 \quad (\lambda = \frac{\varepsilon}{\sigma^2}) \\ &= \frac{\varepsilon^2}{2\sigma^2} \end{aligned}$$

$$\Rightarrow \mathbb{P}\left(\frac{1}{n} \sum_{i=1}^n X_i > \varepsilon\right) \leq \exp\left(-\frac{n \varepsilon^2}{2\sigma^2}\right) = \delta$$

$$\text{w.p. } \geq 1 - \delta \quad \frac{1}{n} \sum_{i=1}^n X_i \leq \sqrt{2\sigma^2 \log(1/\delta)}$$

$$\text{Repeat w/ } -X_i \Rightarrow \mathbb{P}\left(\frac{1}{n} \sum_{i=1}^n X_i < -\varepsilon\right) \leq \exp\left(-\frac{n \varepsilon^2}{2\sigma^2}\right)$$

$$\mathbb{P}\left(\left\{\frac{1}{n} \sum_{i=1}^n X_i > \varepsilon\right\} \cup \left\{\frac{1}{n} \sum_{i=1}^n X_i < -\varepsilon\right\}\right)$$

$$\leq \mathbb{P}\left(\frac{1}{n} \sum_{i=1}^n X_i > \varepsilon\right) + \mathbb{P}\left(\frac{1}{n} \sum_{i=1}^n X_i < -\varepsilon\right)$$

$$\leq \delta$$

$$\Rightarrow \text{w.p. } \geq 1 - \delta \quad \left| \frac{1}{n} \sum_{i=1}^n X_i \right| \leq \sqrt{2\sigma^2 \log(2/\delta)}$$

$$X_i \sim \text{Bernoulli}(p) \quad X_i = \begin{cases} 1 & \text{w.p. } p \\ 0 & \text{w.p. } 1-p \end{cases}$$

$$\begin{aligned} \mathbb{E}[\exp(\lambda X)] &= p e^\lambda + (1-p) e^0 \\ &= 1 - p + p e^\lambda \end{aligned}$$

$$\sup_{\lambda} \lambda \varepsilon - \mathbb{P}_X(\lambda) \leq \begin{cases} \frac{\varepsilon^2}{4p} & p < 1/2 \\ \frac{\varepsilon^2}{4(1-p)} & p > 1/2 \\ 2\varepsilon^2 & p \in [0, 1] \end{cases}$$

Hoeffding's Lemma For a mean-0 R.V. X s.t.

$$X \in [a, b] \text{ almost surely, we have } \log(\mathbb{E}[\exp(\lambda X)]) \leq \frac{\lambda^2 (b-a)^2}{8}$$

Definition A R.V. X is σ^2 -sub-Gaussian if

$$\log(\mathbb{E}[\exp(\lambda X)]) \leq \frac{\lambda^2 \sigma^2}{2}.$$

Corollary If X_1, \dots, X_n are mean-0 σ^2 -sub-Gaussian

$$\text{iid R.V. then } \mathbb{P}\left(\frac{1}{n} \sum_{i=1}^n X_i > \varepsilon\right) \leq \exp\left(-\frac{n \varepsilon^2}{2 \sigma^2}\right).$$

Suppose $X_{i,s} \sim \text{Bernoulli}(\theta_i^*)$ then (by above)

$$\text{we have } \mathcal{E}_i^d = \left\{ \left| \frac{1}{3} \sum_{s=1}^3 (X_{i,s} - \theta_i^*) \right| \leq \sqrt{\frac{\log(4/\delta)}{23}} \right\}$$

w.p. $\geq 1 - \delta/2$ for each i (separately)

w.p. $\geq 1 - \delta$ for both $i \in \{1, 2\}$ simultaneously.

$$\mathbb{P}\left(\bigcup_{i=1}^2 \mathcal{E}_i^c\right) \leq \delta.$$

Rule is play $\arg\max_i \hat{\theta}_i$. So on $\mathcal{E}_1 \cap \mathcal{E}_2$

$$\hat{\theta}_1 \geq \theta_1^* - \sqrt{\frac{\log(4/\delta)}{23}}$$

$$= \theta_2^* + \Delta - \sqrt{\frac{\log(4/\delta)}{23}}$$

$$\theta_1^* - \theta_2^* = \Delta > 0$$

$$\geq \hat{\theta}_2 + \Delta - 2\sqrt{\frac{\log(4/\delta)}{23}}$$

$$\Rightarrow \theta_1^* > \theta_2^* \Rightarrow \hat{\theta}_1 > \hat{\theta}_2 \quad \text{if } 3 \geq \frac{2\log(4/\delta)}{\Delta^2}$$

↑

$$R_T = \Delta E[T_2]$$

$$= \Delta \cdot \mathfrak{S}$$

$$\leq \frac{2 \log(4/\delta)}{\Delta}$$

(choose minimal \mathfrak{S})

$$R_T \leq T \Delta \quad (\text{Trivial})$$

$$R_T \leq \min \left\{ \Delta T, \frac{2 \log(4/\delta)}{\Delta} \right\}$$

$$\leq O(\sqrt{T})$$

(worst case δ)